Big data system analyzing Amazon reviews and reviewers

• Introduction

What we believe, must be mentioned from the get go, is that this task was more in the spectrum of big data **analytics**, rather than the whole concept of big data, which is associated more with managing data and IT infrastructure for serving it. This is the reason why we have been more focused on the idea of accurately predicting which review is fake and which is not. We have also taken the project a step further, rather than just analyzing and evaluating a single review/reviewer, we analyze whole products and modify their overall score based on the "fakes" we find. Python was our so called "weapon" in this fight, and we have used a multitude of libraries for different targets, such as 'sqlite', 'flask', 'numpy', 'json', 'shutil', 'pandas', 'matplotlib', 'os', 'time', and 'math'. Everything was done through python, from the ingestion, to the processing and to the loading onto the website. Our choice for data storage was SQL, more specifically SQLite, which we will justify in the upcoming chapters.

In order to categorize modify the overall score, we have 2 layers of complexity regarding the issue, the "overall" layer, which takes into consideration all the reviews and all the reviewers, and the "individual" layer, which takes into consideration individual user behavior and the way it affects the grade.

• Architecture diagram

We highlight the fact that the project was mainly based on solving the issue at hand, which was actually finding a way of discovering fake reviews/reviewers, rather than focusing solely on the infrastructure part. We will say from the beginning that our system is not scalable horizontally, rather just vertically, or at least in this state it is. The bigger view of this project would have to do with actually connecting to Amazon API and continuously receive reviews from there which are not yet present in our database. This could be done using Redis, where we would store the new reviews/reviewers, and upload them in the SQL database on a daily basis – the tables were created in such a way that they would allow for further updating and adding new data, no matter how big, without impeding the programming part of the project, even though writing might be slow, the query results will be fast. Another thing that must be said is that our algorithm works entirely on statistics and on the idea that what is average rules overall. This will be mentioned again in the next paragraphs, but scaling horizontally could have been done using Spark, but being honest, it felt like it was and still is a bit over our heads. Also, the message queue at the beginning was actually done through a simple … message queue, given the fact that we take in one record at a time, pre-process it and send it down the pipeline, and repeating this until the database is full. This could have been done through kafka, thus allowing parallelization, but we felt that perhaps too complicated given our focus on trying to solve the issue of finding fake reviews/reviewers.. All of this has been an overly-simplified view of the architecture, given the fact that we have not focused as much on that, as we have focused on the analytical issue at hand.

- ## <u>Data Ingestion</u>

Data ingestion is actually done through python, where we have unknowingly created an ETL pipeline, only to later learn about it, reading line after line from a

"json" file. The "json" file was actually the key factor in deciding not to use other ingestion methods, such as Kafka, or MQTT which have been presented in the course. Having a well-defined file (in the sense that all the data was written in different files on the github we have been provided with), gave us the assurance we needed regarding the flow of the incoming data, which was not variable in any way, because, obviously, we were controlling how fast the data was coming in, and that was line by line.

The raw data had a lot of fields: Overall score, Verified Flag, Review Time, Reviewer ID, Product ID, Style, Reviewer Name, Review Text, Summary, unixReviewTime, out of which some were redundant and would have only occupied space. So this is were we go through the process of transformation (eTl) extracting the important information, such as a datetime type of date, after having modified the format so that it matches numpy's, the number of words each review has, a scan for incentivized reviews which results in a flag, the "bin" each review will be contained in(bins will be presented later), and the category the product belongs to. So we drop the style, the summary, the whole text, and the unixReviewTime, thus trimming our data. The last part is loading (etL), which is simply done through the 'sqlite' library, allowing us to populate tables with the transformed data. Next we will explain why we have chosen SQL.

- ## <u>Data Storage</u>

For storing data, we have FIRST chosen SQL, given the fact that we had to compute rather complex queries, which would have been much harder using NOSQL databases.(After the last labs, we have realized it would have been so much wiser to use Spark, but we had no idea at the beginning of the project, and transitioning would have been too complicated in this low interval of time). Another reason would be the clear structure of every file, which was repeated for every category of products. Therefore, we were assured that we always get the same type of input which we are able to insert into the database after transforming. And, in other to achieve full transparency, we choose SQL because we felt both of us were more fluent in this and would be able to achieve a better result. We have also indexed the Review table, so we have faster queries.

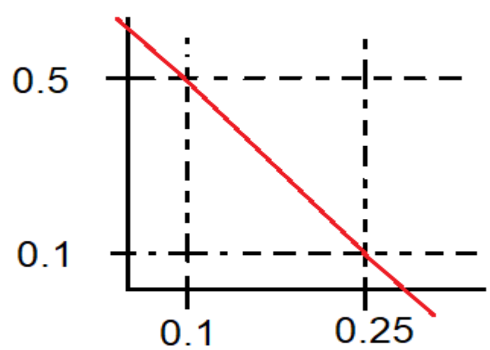
Why SQLite and not MySQL? Simply because the project has been treated as a toy example, where we wanted to test the results and wanted to achieve faster enquiries and access to the database, and we have done this through SQLite. Given the fact that the app only runs on our machines, this amplifies the speed. We do however know that for a larger app, with multiple users MySQL pays off in terms of writing (it does not hog the table by locking it when someone is writing inside), even though it has a slower connection.

• Data Processing

We believe that this part is the bread and butter of our project. Previously, the idea of two layers of complexity has been brought up. We will first start with the "overall" layer.

The first criteria of analysis is based on the word count distribution. This has been one of the complex queries, given that it requires pivoting. The concept behind this is: we have a number of 10 bins, which contains the frequency of reviews with a certain number of words (0-15, 15-30, 30-45, …, 100+). We compare the overall category distribution(the category to which the product belongs), to the distribution created by the reviews of our product. And here , we split the problem in two parts:

a) A number of reviews higher than 25 (mathematical statistics teach us that a sampled quantity higher than 25 yields a distribution similar to the bigger quanity). In this case, we take into consideration two factors, the percentage of mis-distributed reviews, and the difference between the normally-distributed and mis-distributed. A review is counted as mis-distributed once it's frequency is 1.4 times higher than the category's. We do the final check using a linear function which has some user-defined values which it uses as limits for normality. The graph below explains it:



Anything beyond the red line is counted as fake. The red line is computed based on the limit points we were talking about.

b) The other case is the one were the number of reviews is lower than 25. In this situation, we use the big numbers law. We compute the category mean and standard deviation for the number of words, then we check how many of the reviews are outliers in terms of number of words (they're bigger or smaller than 2 times the standard dev). If the percentage of those is higher than 0.2, we simply return a warning, but we do not have enough data to accurately decipher the meaning of the warning.

The second criteria is the verified/unverified results. Here we compute how the unverified reviews affect the overall score. This procedure is much simpler, because unverified reviews have a much lower confidence "score" in our eyes, so if the absolute difference between the score with unverified reviews and the one without unverified reviews is higher than 0.1, we just delete all the unverified reviews. Another issue is having only unverified reviews, where we can obviously keep going with the algorithm, but this is a big enough question mark so that we just don't and return a big failure mark.

The third criteria is really similar to the second, it just analyses the incentivized/non-incentivized reviews. Amazon has a very strict policy which mentions that if a reviewer is incentivized, he must mention so in the review itself. Therefore, we check for the incentivized reviews, we do exactly the same operation as above and we eliminate the strange ones.

The fourth criteria is called rating trend. This one is tightly knit with an "individual" layer criteria, but we will explain it here nevertheless. It simply analyses the time when different users have reviewed the product, and if it so happens that multiple people have reviewed the product exactly in the same day – which would obviously be a distortion in the normal distribution – (just as above, we do check if a day is an outlier by comparing it to 2 times the standard deviation of the distribution) we mark the day as "suspicious", and leave it for further investigation in the next phase.

Here we move on to the second layer of complexity, which is the "individual layer". Here we see the impact each user's behavior has on the final score.

The first criteria is called User Ease. This one takes into consideration how easy each user gives a grade, in the sense that a rather critique user who only gives ratings of 3 and 4 will have a higher say in the final grad than an "easy" user who always gives ratings of 5. So we just divide the "category ease" by the "user ease", and that's the coefficient we multiply the review's rating with. Besides this, Amazon policy allows users to rate the same product multiple times if they purchase it multiple times, but this results in really biased reviews. Therefore, we do an average of each user's score for the product and use it once, instead of using every value(we minimize the impact).

The second criteria is called User Overlapping History, and the concept behind it is based on the fact that users who have a higher overlapping history(compared to the average of each product), might be users paid by third parties who are also paid by companies to promote their products. The comparison criteria is just as above, outliers higher than twice the standard deviation.

The third and final criteria is called User Behaviour and is entwined with the Rating Trend. It is based on 4 flags:

-flag_post_day, which tells you how many reviews per day the user posted, we expect it to be around 1 or 2 per day, anything above that is classified as suspicious

-flag_number_verified, which tells you the amount of unverified reviews a user posts, which basically means he's reviewing with no idea about the product

-flag_verified_rating, the difference a user has between average rating with and without verified reviews; if higher than 0.1 => suspicious

-more_revs_one_prod, tells you the user has a tendency of reviewing the same product multiple times and that his opinion tends to be biased.

If all 4 of these flags have a TRUE value, we classify the user as fake and just ignore the review/s completely. If 3 of them are true, we compare the days in which he has a suspicious activity (more than 3 posts per day), to the days in which the rating trend of the product has a weird activity (higher than mean + 2 std devs), and if the day in which the user reviewed the product is at the intersection of the 2 aforementioned categories, once again, we just normalize the rating of the review to the category norm.

• Conclusions

We conclude by saying that the analytical part of the project works fine, giving out steady results, and we will attach a link to a github repo where you can see the actual results and a few pictures to have a better understanding of our final goal.

We are aware of the fact that from the big data infrastructure/architecture our project is rather shabby, but even so, we would not call it bad, given the statistical models and basically the ideas we have implemented in our algorithm. We could have improved by ingesting data using Kafka(but that would have been overkill given our well-defined data source chunk files), and we should have used Spark in order to have a horizontal scaling. We could have also implemented, just as we mentioned before, another Redis database which would deal with the streaming of new data in the database, if we wanted to have a direct communication with the Amazon API. Also, being totally transparent, the code was not written for somebody else to read it, it was written to deliver a solution to a problem, so we apologise for how ugly it looks. If needed, we are more than willing to pay for a cloud host and set up the website online so that you can see the final product without us presenting it. Thank you for your attention.

https://github.com/mrswad/BigDataLink_Switch/tree/master/Rating_Trends_and_Word_Count_Comparison

https://github.com/mrswad/BigDataLink_Switch/tree/master/Web_Pictures

The links above are pictures that show how the program behaves, and a few exs of criterias we used .